Characterizing Oscillatory Bursts in Single-Trial EEG Data

KH Knuth[1], AS Shah[2], P. Lakatos[2,3], CE Schroeder[2,3]

[1]Computational Sciences Division, NASA Ames Research Center, Moffett Field, CA 94035

[2]Department of Neuroscience, Albert Einstein College of Medicine, Bronx, NY 10461

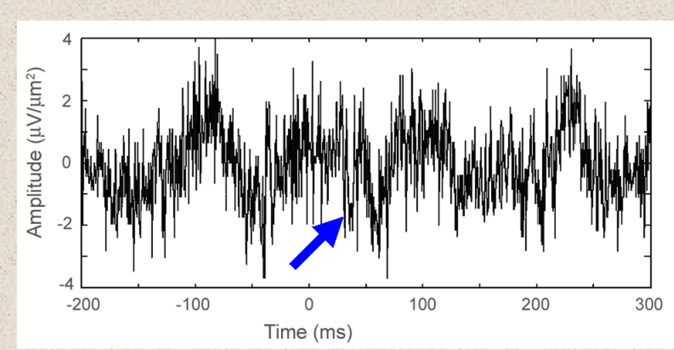
[3]Cognitive Neuroscience & Schizophrenia Program, Nathan Kline Institute, Orangeburg, NY 10962

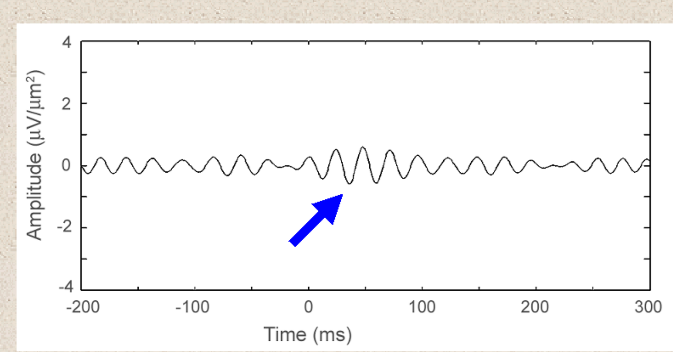
Oscillatory bursts

Oscillatory bursts in numerous bands ranging from low (theta) to high frequencies (e.g., gamma) undoubtedly play an important role in cortical dynamics. Largely because of the inadequacy of existing analytic techniques, however, oscillatory bursts and their role in cortical processing remains poorly understood. To study oscillatory bursts effectively one must be able to isolate them and characterize them in the single trial. We describe a series of straightforward analysis techniques that produce useful indices of burst characteristics. First, stimulus-evoked responses are estimated using Differentially Variable Component Analysis (dVCA), and are subtracted from the single-trial. The single-trial characteristics of the evoked responses are stored to identify possible correlations with burst activity. Time-frequency (T-F), or wavelet, analyses are then applied to the single trial residuals. While T-F plots have been used in recent studies to identify and isolate bursts, we go further by fitting each burst in the T-F plot with a two-dimensional Gaussian. This provides a set of burst characteristics, such as, center time, burst duration, center frequency, frequency dispersion, and amplitude, all of which contribute to the accurate characterization of the individual burst. The burst phase can also be estimated. Burst characteristics can be quantified with several standard techniques (e.g., histogramming and clustering), as well as Bayesian techniques (e.g., blocking) to allow a more parametric analysis of the characteristics of oscillatory bursts, and the relationships of specific parameters to cortical excitability and stimulus integration.

Identifying Bursts

Identifying oscillatory bursts in raw data is extremely difficult. The trace below derived from an intracortical visual-evoked field potential trace has a gamma band burst at 50 ms. (This trace is actually a current source density (CSD) derivation from a multielectrode array, hence the units are $\mu V/\mu m^2$)





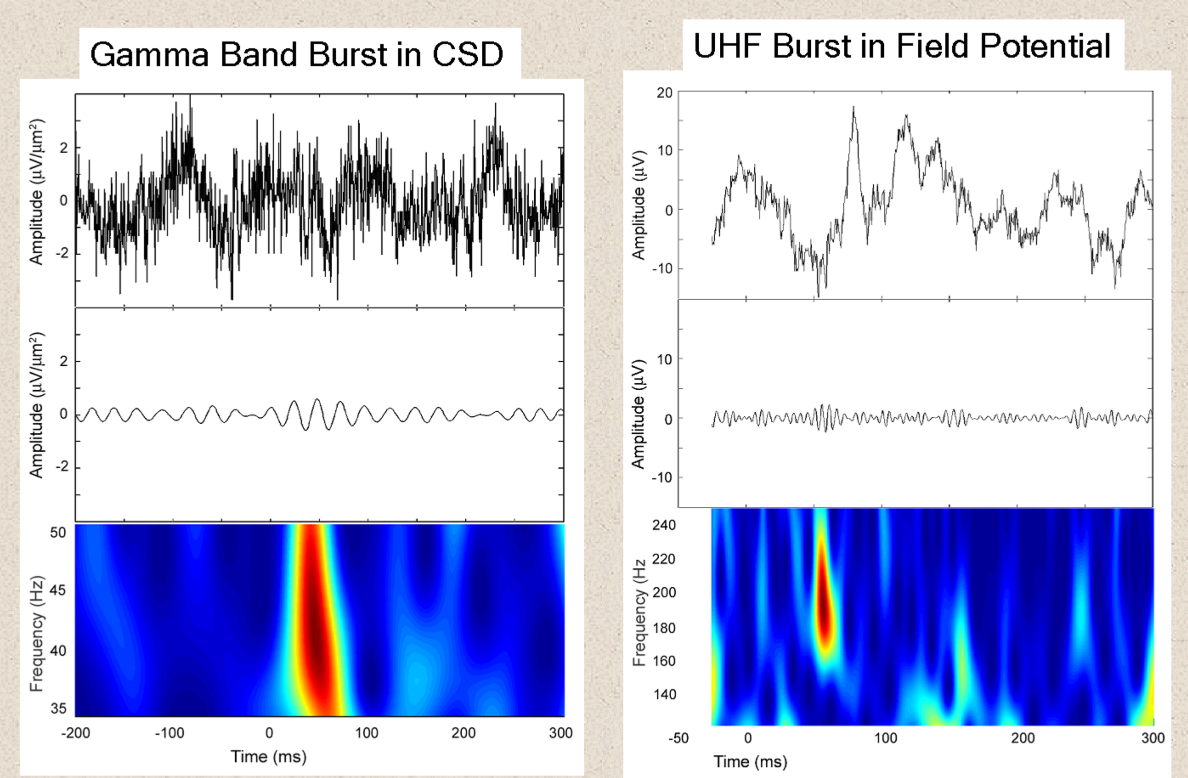
Bandpass filtering the trace at a center frequency of 40 Hz reveals the oscillatory burst.

However, noise makes their identification difficult since other activity often spills into the frequency range of interest.

Time-Frequency Plots

Time-Frequency (T-F) (or wavelet) methods can be significantly more revealing. Note that the oscillatory bursts are characterized by islands of activity isolated in both time and frequency.

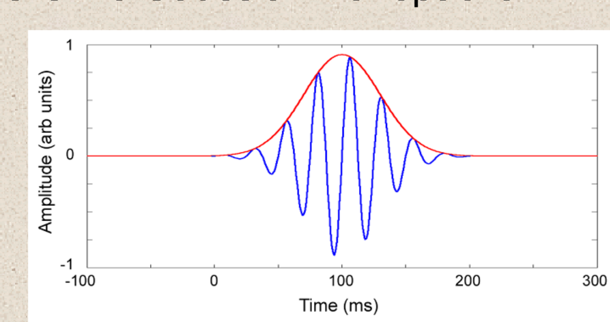
Below **left** is our previous example of a gamma band burst in a CSD trace. On the **right** is an ultra-high frequency (UHF) burst in an intracortical visual-evoked field potential.



Time-frequency methods are clearly superior to standard Fourier techniques in enabling us to isolate oscillatory bursts. We now take this a step further.

Modeling a Burst

Mathematically, we model an oscillatory burst as a Sine Wave with a Gaussian envelope. This is the Gaussian wavepacket model



This enables us to describe each burst with a set of burst parameters.

Amplitude — Center (peak) Time — Center (peak) Frequency

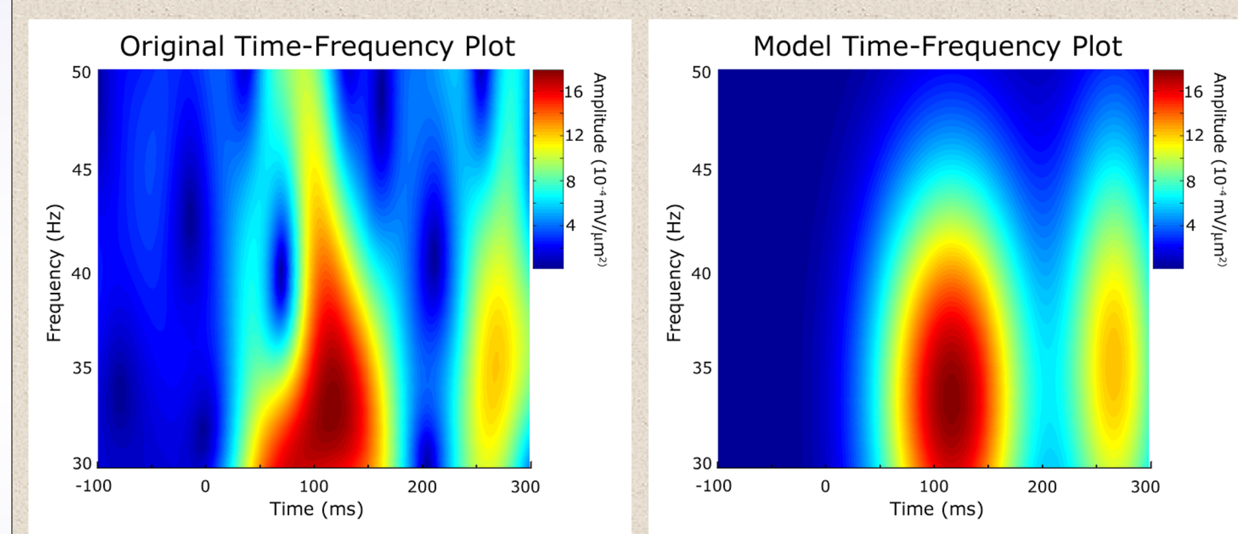
$$B(t) = A\exp\left(-\frac{(t-t_o)^2}{2\sigma_t^2}\right)\sin(2\pi f_o t - \phi)$$

Duration (temporal dispersion) — Phase

Isolating and Characterizing Bursts

With this model, we can characterize the bursts using the T-F results. First a threshold is determined by estimating the noise level (sigma) in the T-F data. A peak finding algorithm identifies the peaks of the bursts in the T-F plot that are above the noise floor by 2 sigma. A two-dimensional Gaussian is fit to each peak. The result is a set of burst parameters with values consistent to the Gaussian wavepacket model.

On the left is the original T-F plot, and on the right is the T-F plot reconstructed from the Gaussian wavepacket model.

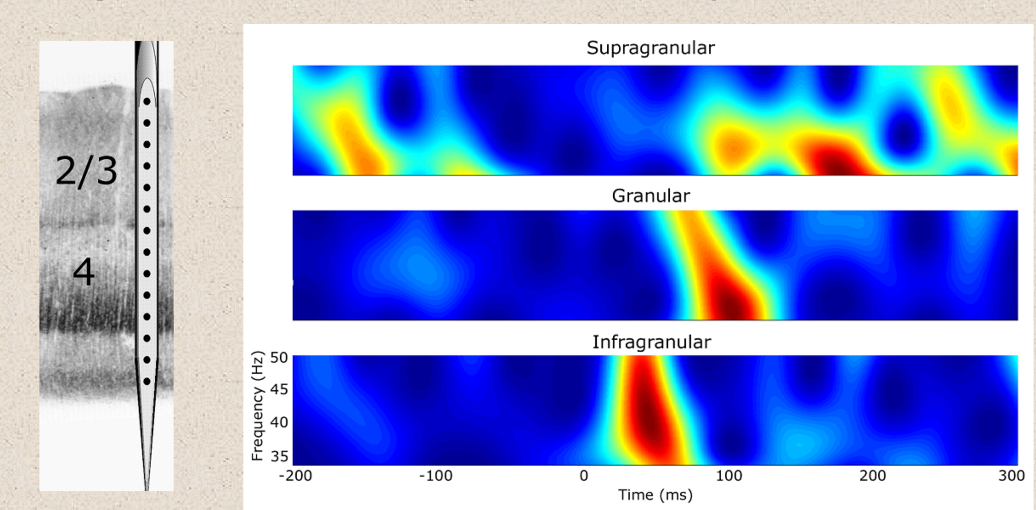


The burst parameters are listed below (amplitude and phase omitted). Note that the time dispersion (duration) is related to the frequency dispersion via the uncertainty principle.

	t_o	f_o	σ_t	σ_f
BURST 1	116.7 ms	33.4 Hz	51.1 ms	8.1 Hz
BURST 2	268.6 ms	35.2 Hz	35.5 ms	8.8 Hz

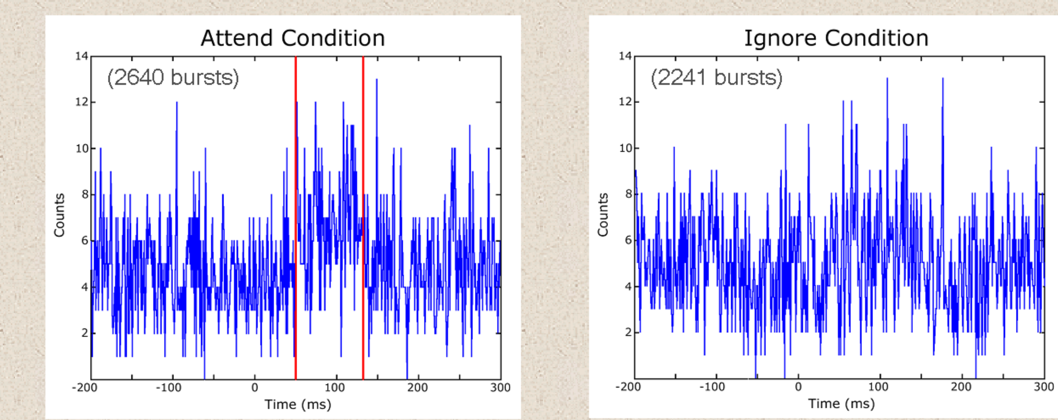
Distribution across Cortical Layers

Using a diffuse red light flash, intracortical field potentials were recorded from a linear multielectrode array spanning the cortical layers in macaque V1 (Mehta et al 2000). After estimating and removing the evoked responses using dVCA, the CSD profile of the residuals was derived and the bursts were analyzed. Bursts occurring in distinct cortical layers can easily be characterized.



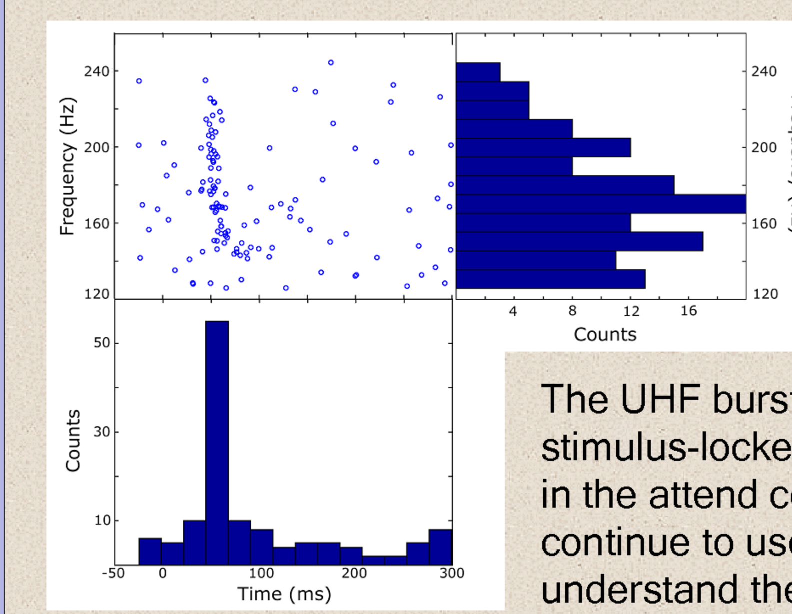
Gamma-Band Burst Example

In this example we examine the statistical properties of the burst parameters for bursts in the gamma band range. The data were recorded from V4 during a visual attention task. The histogram shows the number of bursts during each time bin.



Bayesian Blocks (Scargle, NASA Ames) was used to identify change points. Only in the attend condition is there a significant increase in the number of gamma band bursts from about 50-130 ms.

UHF Burst Example



Here we examine the characteristics of the UHF bursts. The histograms show most bursts occur around 50 ms with a peak frequency of 170 Hz.

The UHF bursts are clearly more stimulus-locked than the gamma bursts in the attend condition above. We continue to use these methods to better understand these new responses.

Summary

We have presented a new analysis technique to identify and characterize oscillatory bursts. The analysis is based on a **Gaussian wavepacket model** of the burst and the result of the analysis is a set of **burst parameters** for each burst. These parameters can be used to distinguish different classes of bursts, correlate burst properties with details of the experimental task, relate bursts to the single-trial characteristics of the evoked componentry, and study burst-burst interactions. The preliminary examples presented here are only a sample of the possibilities that these techniques will afford.

Acknowledgements

We thank Dr. Istvan Ulbert, Dr. Ashesh Mehta, Tammy McGinnis, Noelle O'Connell, Aimee Mills, Dr. Mingzhou Ding, Dr. Steven Bressler, and Dr. Leonard Trejo. The work was supported by the NASA IDU/IS/CICT Program, NASA Aerospace Technology Enterprise, NIH MH61989 and MH60358, and Medical Scientist Training Program (T32M07288).

Info on differentially variable component analysis (dVCA) can be found on http://www.huginn.com/knuth/publications.html

Please visit our talk **717.9** and our poster **752.7** for more on our work with oscillations and oscillatory bursts.